DEFENCE R&D DÉFENSE

Emitter Number Detection Based on Intrapulse Information and Application of the Information Theoretic Criteria

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DEFENCE RESEARCH ESTABLISHMENT OTTAWA

TECHNICAL REPORT
DREO TR 2000-012
February 2000

Project
1AC11

ABSTRACT

In Electronic Support Measures (ESM) systems, intrapulse analysis has gained much interest in the development of pulse train deinterleaving techniques due to its ability to handle complex radar signals. In this report, an approach for detecting the number of emitters is proposed based on the use of intrapulse information of the intercepted pulse trains. The approach is an application of the information theoretic criteria. It exploits the fine intrapulse modulation information of emitter signal and has the advantage of not requiring a subjective threshold setting. The approach is statistically consistent and computationally efficient. Computer simulations and real sensor data are used to demonstrate the effectiveness of the proposed approach.

RÉSUMÉ

Dans les systèmes de mesures de support électroniques (MSE), l'analyse de l'intrapulse a sucité beaucoup d'intérêt dans le contexte du développement des techniques de désentrelacement de train d'impulsions due à sa capacité de manipuler les signaux complexes de radar. Dans ce rapport, nous proposons une approche pour détecter le nombre d'émetteurs qui est basée sur l'utilisation d'information sur l'intrapulse des trains d'impulsions. L'approche est une application direct d'un des critères de la théorie de l'information. Elle exploite l'information fine des modulations de l'intrapulse du signal émetteur. L'approche est statistiquement consistente, permet un calcul efficace et n'exige aucune configuration subjective d'un seuil. L'efficacité de cette approachae été démontrée en utilisant des données simulées et réelles.

EXECUTIVE SUMMARY

Background: Conventional deinterleaving techniques are usually based on the use of coarse parameters such as angle-of-arrival (AOA), radio frequency (RF), time-of-arrival (TOA), pulse width (PW), pulse repetition interval (PRI) and polarization. They encounter difficulties when faced with the proliferation of radar signals and modern radars employing sophisticated waveforms. As a result, there is a requirement to exploit the use of intrapulse information in the development of pulse train deinterleaving techniques.

Results: In this report, we discuss the application of the information theoretic criteria to the emitter number detection problem in pulse train deinterleaving process.

- A computationally efficient approach for detecting the number of emitters is proposed based on the use of the intrapulse information of the intercepted pulsed signals and the application of the information theoretic criteria.
- Performance analysis is carried out and it is shown that the proposed approach is statistically consistent.
- Computer simulations and real sensor data are used to demonstrate the effectiveness of the proposed approach.

Significance: The proposed approach is based on the use of intrapulse information of the intercepted pulse trains and has the ability to handle complex radar signals. The algorithm is computationally more efficient than other methods such as the technique of hypothesis testing and the cluster validity methods. In addition, fast algorithms can be used, making it suitable for real time applications. The proposed approach also has the advantage of not requiring a subjective threshold setting which enables the reduction of the amount of human intervention for an autonomous ESM system.

Zhou, Y. and Lee, J. P. Y., Emitter Number Detection Based on Intrapulse Information and Application of the Information Theoretic Criteria, Defence Research Establishment Ottawa, DREO Report TR 2000-012, February 2000

SOMMAIRE

Introduction: Des techniques de désentrelacement conventionnelles sont habituellement basées sur l'utilisation des paramtres bruts tels que l'angle d'arrivée (AOA), la fréquence radio (RF), le temps d'arrivée (TOA), la largeur d'impulsion (PW), l'intervalle de répétition d'impulsions (PRI) et la polarisation. Ils rencontrent des difficultés une fois confrontés à la prolifération des signaux de radar et des radars modernes utilisant des formes d'onde sophistiquées. En conséquence, il y une motivation pour exploiter l'utilisation d'information sur l'intrapulse dans le développement des techniques désentrelacement des de trains d'impulsion.

Résultats: Dans ce rapport, nous discutons l'application des critères de la theorie de l'information au probléme de détection de nombre d'émetteur dans le processus de désentrelacement de train d'impulsion.

- On propose une approche de calcul efficace pour détecter le nombre d'émetteurs a basé sur l'utilisation d'information d'intrapulse des signaux pulsés interceptés et de l'application des critères de la theorie de l'information.
- L'analyse d'exécution est effectuée et on démontre que l'approche proposée est statistiquement conforme.
- Des simulations sur l'ordinateur sur des vraies données de capteur sont employées pour démontrer l'efficacité de l'approche proposée.

Signification: L'approche proposée est basée sur l'utilisation d'information sur intrapulse des trains d'impulsion interceptés et a la capacité de manipuler les signaux de radar complexes. L'algorithme de calcul est plus efficace que d'autres méthodes telles que la technique de l'hypothèse de test et les méthodes de validité de catégorisation. De plus, des algorithmes rapides peuventêtre utilisés, le rendant approprié pour des applications en temps réel. L'approche proposée a également l'avantage de ne pas exiger une configuration subjective de seuil, ce qui permet la réduction de la quantité d'interposition humaine pour un système autonome d'ESM.

Zhou, Y. et Lee, Y. J. P., Détection De Nombre D'émetteur Basée Sur L'information D'Intrapulse Et Application Des Critères De La Theorie De L'information, Le Centre De Recherches Pour La Défense, Ottawa, CRDO Rapport TR 2000-012, février 2000

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1.0 INTRODUCTION

In ESM systems, receivers are designed to intercept radar signals and perform emitter classification and identification for electronic warfare (EW) purposes. The information provided by an EW receiver through the extraction of radar signal parameters can be used for the collection of electronic intelligence (ELINT) data in strategic situations, or threat warning, and assisting with radar emitter jamming in tactical situations. In practice, since there is usually more than one emitter transmitting pulsed signals in the same signal environment, the intercepted signals are pulse trains interleaved in time. In order for a receiver to characterize the intercepted emitters, deinterleaving techniques must be applied to separate the interleaved pulse trains into individual emitter groups [1][2]. The interleaved pulse trains which belong to a particular emitter are then submitted to the pulse chain characterizer for analysis or used to determine the decision functions by means of one or more training algorithms [3][4][5].

Conventional deinterleaving techniques are usually based on the use of coarse conventional parameters such as angle-of-arrival (AOA), radio frequency (RF), time-of-arrival (TOA), pulse width (PW), pulse repetition interval (PRI) and polarization [1]. They encounter difficulties when faced with the proliferation of radar signals and modern radars employing sophisticated waveforms. Conventional emitter parameters are easy to define in a certain signal environment, but the actual signal arriving at the sensor after the propagation path, sensor and measurement subsystems are often difficult to predict. This will cause inaccuracies in the measurement of the conventional emitters parameters. Furthermore, as computer and digital technologies become more and more powerful, radar systems will employ complex waveform modulation techniques which make deinterleaving based on the use of coarse conventional parameters alone vulnerable. When signals of similar characteristics are compared by using the conventional parameters, ambiguity can occur in both the sorting and identification process. As a result, there is a requirement to exploit the use of intrapulse information for pulse train deinterleaving. Intrapulse information refers to the fine waveform modulation of the radar signals and carries rich information about the emitter system characteristics, signal propagation path and the environment [6]. Intrapulse information has been used by EW engineers for classifying emitters into finer groups [1]. Techniques based on intrapulse information are closely related to unsupervised learning in pattern recognition such as cluster analysis [7], fuzzy clustering algorithms [8] and neural networks based approaches [9][10][11].

Several approaches can be used including the techniques of hypothesis testing

[12], the cluster validity methods [13][14][15] and the approaches based on the application of the information theoretic criteria [16]. The methods of hypothesis testing require that a threshold be set according to some subjective human judgment. This intervention will increase the demand for interactions between command users and the system, and is not suitable for the realization of an autonomous ESM system. The cluster validity approaches use validity functions to measure the effectiveness of the cluster structure. Under different assumed number of clusters centers, the algorithms determine the optimal clustering as the one which has the optimum performance measure. They require a heavy computational burden which makes real-time implementation extremely difficult. The information theoretic criteria refers to the model selection criteria introduced by Akaike (AIC) [17], Rissanen (MDL) [18] and by Schwartz [19]. The criteria take account simultaneously of both the goodness-of-fit (likelihood) of a model and the number of parameters used to achieve that fit. Many important statistical modeling techniques have been developed in statistics [20] and signal processing [21][22].

In this report, we discuss the application of the information theoretic criteria to the emitter number detection problem in the pulse train deinterleaving process. An approach is proposed which uses the intrapulse information of the intercepted signals to determine the number of emitters. The algorithm is computationally efficient and does not require any subjective threshold setting. In the approach, the intercepted signals are down-converted to base-band and represented in analytic forms. The pulse trains are first aligned in time and then arranged in vector forms. The information theoretic criteria is known to take the form of a penalized likelihood function. Since the signal waveforms are assumed to be unknown deterministic, it is difficult to obtain the likelihood function directly. We decompose the pulse data vector into the assumed signal and the noise subspace component. Under the independent and identically distributed $i.i.d$ Gaussian assumption, the noise subspace component is shown to a Gaussian process with zero mean and its probability density function (PDF) can be obtained directly. The conditional distribution of the signal subspace component is obtained using a minimum variance solution of a linear relationship between the signal and the noise subspace component. Under the hypothesis of k emitters, the final maximized likelihood function of the pulse data is derived as a ratio of the arithmetic to the geometric mean of the k smallest eigenvalues of the sample covariance of the pulse data vector. Performance analysis shows that the approach is statistically consistent. The algorithm only depends on the computation of the eigenvalues of the sample covariance matrix of the pulse data, fast algorithms can be used, making it suitable for real time applications.

The report is organized as follows. In Section 2, we formulate the signal pulse model and discuss the pre-processing of the pulse signals. In Section 3, we discuss the application of the information theoretic criterion to the emitter number detection problem. The maximized likelihood function for both the signal and the noise components are derived and the final detection criterion is obtained. In Section 4, we carry out the asymptotic analysis for the proposed approach and show that it is consistent. Finally, in Section 5, computer simulations and real data are used to demonstrate the effectiveness of the proposed approach.

2.0 SIGNAL MODEL FORMULATION

Assume that there are K emitters which transmit narrow-band pulsed signals. The receiver is assumed to be capable of separating simultaneous signals. Once the signals are received, the amplitude, phase and frequency profiles of each pulse are computed and stored in data files. The frequency profile of each pulse is used to remove the carrier frequency and down-convert the signal to base-band. Assuming that the mth pulsed signal is from the kth emitter, the analytic representation of the mth pulse in the base-band can be written as

$$\tilde{x}_m(t) = \alpha_m s_k(t - \tau_m^t) + \tilde{\nu}_m(t), \tag{1}$$

where $s_k(t)$ denotes the complex signal waveforms from the mth emitter, α_m represents the gain and phase uncertainties of the receiver and τ_m^t is the time delay relative to a reference time origin. The signal waveforms $s_k(t)$ are assumed to be unknown deterministic, and $\{s_k(t);\ k = 1, 2, \ldots, K\}$ linearly independent. The input noise process $\tilde{\nu}_m(t)$ includes the external ambient noise, antenna thermal noise and the circuitry noise. However, it is dominated by the circuitry noise since the RF pre-amplifier of the receiver is always designed to have sufficient gain to overcome the additional noise sources in the receiver. The quantization noise introduced by the analog-to-digital converter is another source of noise. In general, $\tilde{\nu}_m(t)$ can be assumed to be an *i.i.d.* Gaussian process with zero mean and an unknown variance of σ_ν^2.

The application of the information theoretic criteria is to measure and compare the intrapulse information of all the received pulses. Thus, all the pulses must be aligned with respect to a reference time origin. Consider the discrete forms of the signal. Let T denote the sampling interval. We assume that the sampling rate is sufficiently high so

that the time delay can be approximated by $\tau_m^t = \tau_m T$, where τ_m is an integer. Then, the discrete version of (1) can be written as

$$\tilde{x}_m(nT) = \tilde{\alpha}_m s_k(nT - \tau_m T) + \tilde{\nu}_m(nT), \tag{2}$$

or simply

$$\tilde{x}_m(n) = \tilde{\alpha}_m(n - \tau_m) + \tilde{\nu}_m(n), \tag{3}$$

where n is the index in time. The time delay τ_m is determined by the threshold setting of the triggering signal and the pre/post trigger adjustment of the digitizer. Due to the changes of the signal environment, system noise and fluctuations of gains and phases of the receivers, perturbations can occur to the time delay of each individual pulse. The removal of the time delays can be done as follows. First, we search for the maximum amplitudes for all the pulses. The averaged peak amplitude of each pulse is computed. All the pulses are aligned to the point at a power level 6-dB below the peak [30]. After the alignment, the pulse data vector becomes

$$x_m(n) = \alpha_m s_k(n) + \nu_m(n), \tag{4}$$

Assume that M pulses have been intercepted. In compact matrix form, model (4) can be written as

$$\underline{x}(n) = A\underline{s}(n) + \underline{\nu}(n), \tag{5}$$

where $\underline{x}(n) = [x_1(n), \ldots, x_M(n)]^T$, $\underline{s}(n) = [s_1(n), \ldots, s_K(n)]^T$, $\underline{\nu}(n) = [\nu_1(n), \ldots, \nu_M(n)]^T$. The noise vector $\underline{\nu}(n)$ is jointly Gaussian distributed with covariance $R_\nu = \sigma_\nu^2 I$, where notation I denotes the identity matrix. The matrix A is called the association matrix of size $M \times K$ given by

$$A = \begin{bmatrix} \alpha_1 & 0 & \dots & 0 & 0 \\ \alpha_2 & 0 & \dots & 0 & 0 \\ 0 & \alpha_3 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & 0 & \alpha_M & 0 \end{bmatrix}. \tag{6}$$

Each row of A has one non-zero entry which associates the received pulsed signal with a particular emitter. For example, if the mth row has a non-zero at the kth column position, it means that the mth pulse is the emission of the kth emitter and its value indicates the complex receiver gain associated with the mth pulse. Since each row of A has only one non-zero element, the columns of A are linearly independent. It follows that A is of full column rank.

3.0 INFORMATION THEORETIC CRITERIA BASED APPROACH

The information theoretic criteria were first introduced by Akaike, Rissanen and Schwartz *et al.* and have been used in data analysis for model selection for many years. In this section, we apply the information theoretic criteria to the problem of detecting the number of emitters for pulse train deinterleaving.

3.1 Information theoretic criteria

When applied to the model selection problems, the information theoretic criteria take into account both the goodness-of-fit (likelihood) of a model and the number of parameters used to achieve that fit. In general, the criteria take the form of a penalized likelihood function, i.e., a negative log likelihood function plus a penalty function. From the information point of view, the likelihood function represents the information gained from the data while the penalty function represents the uncertainty introduced by the unknown parameters. The penalty function is proportional to the number of parameters used in the probabilistic model. For a set of observations and a family of models, the application of the information theoretic criteria is to find the one that minimizes the criterion.

Given the set of pulsed signals $\mathbf{X} = \{\underline{x}(1), \underline{x}(2), \dots, \underline{x}(N)\}$, the information

theoretic criterion is given by

$$C = -\log L(\mathbf{X} \mid \hat{\Theta}) + b\,[p(k), N], \tag{7}$$

where $\hat{\Theta}$ is the maximum likelihood estimate of model parameter Θ, L is a family of conditional PDFs, $p(k)$ denotes the number of parameters which can freely adjusted in Θ and $b\,[p(k), N]$ is the penalty function. The penalty function takes different forms depending on the criterion used. For the Akaike's AIC, the penalty function is $p(k)$ itself, i.e., $b_A[p(k), N] = p(k)$. The penalty functions of the The Rissanen's MDL and Schwartz's criteria are given by

$$b_M[p(k), N] = \frac{1}{2}\log\left[\frac{N+2}{24}\right]p(k) + \log(k+1), \text{ and } b_S[p(k), N] = \frac{1}{2}p(k)\log N, \tag{8}$$

respectively. In the large sample limit, when ignoring the constant terms, the MDL and the Schwartz's criterion are essentially the same with the penalty function given by $b\,[p(k), N] = \frac{1}{2}p(k)\log N$. Among the criteria, the MDL and the Schwarts's criterion both produce consistent order estimates while the AIC does not [17][18][19][23]. The inconsistency of the AIC is due to the fact that the penalty function of the AIC does not depend on the number of samples. A consistent criterion should have a penalty function which depends on the number of samples. It should be noted, however, that statistical consistency is an asymptotic property. For real problems which usually have finite sample sizes, other performance measures may also be very important.

3.2 Pulse data vector decomposition

Since the pulse data vector contains the unknown deterministic signal waveforms $\underline{s}(n)$, it is difficult to write the likelihood function directly. Consider a decomposition of the pulse data vector $\underline{x}(n)$. In the absence of noise, it can be seen that $\underline{x}(n)$ is confined to the column range space of A. Define the column range space as the signal subspace. We can verify that the dimension of the signal subspace is K. Define the $(M-K)$ dimensional complementary subspace of the signal subspace as the noise subspace. If we decompose $\underline{x}(n)$ into its components in the signal and the noise subspace, we have

$$\underline{x}(n) = U \begin{bmatrix} \underline{x}_S(n) \\ \underline{x}_N(n) \end{bmatrix}, \tag{9}$$

where $\underline{x}_S(n)$ is the $K \times 1$ signal subspace component, $\underline{x}_N(n)$ is the $(M-K) \times 1$ noise subspace component, and U denotes a unitary coordinate transformation matrix. The unitary matrix U can be partitioned as $U = [U_S, U_N]$, where the columns of U_S and U_N form the set of orthonormal basis of the signal and the noise subspace, respectively. The signal and the noise subspace components can be calculated as

$$\underline{x}_S(n) = U_S^H \underline{x}(n), \text{ and } \underline{x}_N(n) = U_N^H \underline{x}(n). \tag{10}$$

We also have the following relationships

$$P_A \underline{x}(n) = U_S \underline{x}_S(n) \text{ and } P_A^{\perp} \underline{x}(n) = U_N \underline{x}_N(n), \tag{11}$$

where $P_A = A(A^H A)^{-1} A^H$ and $P_A^{\perp} = I - P_A$ denote the projection operator onto the signal and the noise subspaces, respectively.

3.3 Information theoretic criteria for emitter number detection

Denote $X_N = \{\underline{x}_N(1), \underline{x}_N(2), \ldots, \underline{x}_N(N)\}$ and $X_S = \{\underline{x}_S(1), \underline{x}_S(2), \ldots, \underline{x}_S(N)\}$. Under the *i.i.d* Gaussian assumption, the PDF of $\{X_S, X_N\}$ can be written as a product of the marginal PDFs

$$\begin{aligned} L\{X_S, X_N\} &= \prod_{n=1}^{N} L\{\underline{x}_S(n), \underline{x}_N(n)\} \\ &= \prod_{n=1}^{N} L\{\underline{x}_N(n)\} \prod_{n=1}^{N} L\{\underline{x}_S(n) \mid \underline{x}_N(n)\}. \end{aligned} \tag{12}$$

It can be verified that the noise subspace component $\underline{x}_N(t)$ is a zero mean Gaussian with covariance $R_{NN} = \sigma_\nu^2 I$, where I is an identity matrix of size $(M-k) \times (M-k)$ under

the hypothesis of k emitters. The PDF of X_N can be written as

$$\begin{aligned} L\{X_N\} &= \prod_{n=1}^{N} L\{\underline{x}_N(n)\} \\ &= \left\{\pi^{M-k}\, det(R_{NN})\right\}^{-N} \exp\{-\sum_{n=1}^{N} \underline{x}_N^H(n) R_{NN}^{-1} \underline{x}_N(n)\} \qquad (13) \\ &= \left\{\pi^{M-k}\, det(R_{NN})\right\}^{-N} \exp\{-\sigma_\nu^{-2} \sum_{n=1}^{N} \underline{x}_N^H(n) \underline{x}_N(n)\}, \qquad (14) \end{aligned}$$

where *det* denotes the determinant. It can be seen that $L\{X_N\}$ contains one single unknown parameter σ_ν^2. The maximum likelihood estimate of σ_ν^2 can be obtained by maximizing $L\{X_N\}$ with respect to σ_ν^2 as

$$\hat{\sigma}_\nu^2 = \frac{1}{M-k} tr\{\hat{R}_{NN}\}, \qquad (15)$$

where tr denotes the trace operator, $\hat{R}_{NN} = U_N^H \hat{R}_x U_N$ and $\hat{R}_x$ is the sample covariance of the pulse data vector

$$\hat{R}_x = \frac{1}{N} \sum_{n=1}^{N} \underline{x}(n) \underline{x}^H(n). \qquad (16)$$

Substituting $\hat{\sigma}_\nu^2$ back into $L\{X_N\}$ yields

$$L\{X_N\} = (\pi e)^{-N(M-k)} \left\{\frac{1}{M-k} tr\{U_N^H \hat{R}_x U_N\}\right\}^{-N(M-k)} \qquad (17)$$

In (17), it can be seen that the maximized likelihood function is determined by the selection of the orthonormal basis of the noise subspace. Consider the eigen-decomposition of the sample covariance $\hat{R}_x$

$$\hat{R}_x = \sum_{i=1}^{M} \hat{\lambda}_i \hat{\underline{u}}_i \hat{\underline{u}}_i^H, \qquad (18)$$

where $\{\hat{\lambda}_i, \underline{\hat{u}}_i\}$ denotes the eigenvalues and corresponding eigenvectors of $\hat{R}_x$. The eigenvalues are arranged in decreasing order, i.e., $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \hat{\lambda}_3 \ldots$. It can be verified [24] that the column orthonormal matrix U that maximizes the quadratic $L\{X_N\}$ is given by $\hat{U}_N = [\underline{\hat{u}}_{k+1}, \underline{\hat{u}}_{k+2}, \ldots, \underline{\hat{u}}_M]$. That is, the maximum likelihood estimate of the noise subspace is spanned by the eigenvectors $\{\underline{u}_i;\ i = k+1, k+2, \ldots, M\}$, and the estimated signal subspace is spanned by the first k eigenvectors of $\hat{R}_x$, $\{\underline{u}_i;\ i = 1, 2, \ldots, k\}$. The maximized $L\{X_N\}$ then becomes

$$L\{X_N\} = (\pi e)^{-N(M-k)} \left\{ \frac{1}{M-k} \sum_{i=k+1}^{M} \hat{\lambda}_i \right\}^{-N(M-k)} . \tag{19}$$

To determine the conditional PDF of $\{x_S\}$, we use the following linear prediction relationship between the signal and the noise subspace component

$$\underline{x}_S(n) = B\underline{x}_N(n) + \underline{\epsilon}(n), \tag{20}$$

where B is a matrix of $(M-k) \times k$. The optimal B can be obtained as the following minimum variance solution

$$B_{opt} = \arg\min_B E\{[\underline{x}_S(n) - B\underline{x}_N(n)]^H [\underline{x}_S(n) - B\underline{x}_N(n)]\}. \tag{21}$$

Using the principle of orthogonalization [25],

$$B_{opt} = R_{SN} R_{NN}^{-1}, \tag{22}$$

where $R_{SN} = E\{\underline{x}_S(n)\underline{x}_N^H(n)\}$. R_ϵ denotes the covariance of $\underline{\epsilon}(n)$ and is given by $R_w = R_{SS} - R_{SN}R_{NN}^{-1}R_{NS}$, where $R_{NS} = E\{\underline{x}_N(n)\underline{x}_S^H(n)\}$. Given the noise subspace component $\underline{x}_N(t)$, we can consider $\underline{x}_S(n)$ as a Gaussian random process with a mean of $B_{opt}\underline{x}_N(t)$ and a covariance R_w. Thus, the conditional PDF of X_S can be written as

$$L\{X_S \mid X_N\} = \prod_{n=1}^{N} L\{\underline{x}_S(n) \mid \underline{x}_N(n)\} = \left\{\pi^k \, det(R_w)\right\}^{-N} \exp\{-\sum_{n=1}^{N} \underline{\epsilon}^H(n) R_w^{-1} \underline{\epsilon}(n)\}. \tag{23}$$

where $\underline{\epsilon}(n) = \underline{x}_S(n) - B_{opt}\,\underline{x}_N(n)$ denotes the prediction residual. We consider the maximization of the likelihood function $L\{X_S \mid X_N\}$ with respect to $\{R_{SS}, R_{NS}, R_{SN}\}$. A necessary and sufficient condition is that R_w satisfies the following equation [26]

$$\hat{R}_\epsilon = \frac{1}{N}\sum_{n=1}^{N}[\underline{x}_S(n) - B_{opt}\,\underline{x}_N(n)]^H[\underline{x}_S(n) - B_{opt}\,\underline{x}_N(n)]. \tag{24}$$

Since $R_w = R_{SS} - R_{SN}R_{NN}^{-1}R_{NS}$, by comparing the terms at both sides of (24), we can obtain

$$\hat{R}_{NS} = \frac{1}{N}\sum_{n=1}^{N}\underline{x}_N(n)\underline{x}_S^H(n),\ \ \hat{R}_{SN} = \frac{1}{N}\sum_{n=1}^{N}\underline{x}_S(n)\underline{x}_N^H(n),\ \text{ and }\ \hat{R}_{SS} = \frac{1}{N}\sum_{n=1}^{N}\underline{x}_S(n)\underline{x}_S^H(n). \tag{25}$$

Substituting (25) back into (23) yields the maximized $L\{X_S \mid X_N\}$

$$L\{X_S \mid X_N\} = (\pi e)^{-kN}\{det(\hat{R}_w)\}^{-N} = (\pi e)^{-Nk}\{det(\hat{R}_{SS} - \hat{R}_{SN}\hat{R}_{NN}^{-1})\}^{-N}. \tag{26}$$

Finally, the joint distribution $L\{X_S, X_N\}$ can be written as

$$L\{X_S, X_N\} = (\pi e)^{-NM}\{det(\hat{R}_{SS} - \hat{R}_{SN}\hat{R}_{NN}^{-1})\}^{-N}\left\{\frac{1}{M-k}\sum_{i=k+1}^{M}\hat{\lambda}_i\right\}^{-N(M-k)}. \tag{27}$$

From the eigen-decomposition of $\hat{R}_x$, we can write the sample covariance of $\underline{x}(t)$ as

$$\hat{R}_x = U\begin{pmatrix}\hat{R}_{SS} & \hat{R}_{NS}\\ \hat{R}_{SN} & \hat{R}_{NN}\end{pmatrix}U^H. \tag{28}$$

Since U is a unitary matrix and $det(\hat{R}_x) = det(\hat{R}_{NN})det(\hat{R}_{SS} - \hat{R}_{SN}\hat{R}_{NN}^{-1})$, we have

$$det(\hat{R}_{SS} - \hat{R}_{SN}\hat{R}_{NN}^{-1}) = det(\hat{R}_x)/det(\hat{R}_{NN}), \tag{29}$$

and $L\{X_S(n), X_N(n)\}$ can be further written as

$$L\{X_S, X_N\} = (\pi e)^{-NM}\{\Gamma(k)\}^{-N(M-k)}, \tag{30}$$

where $\Gamma(k)$ is the ratio of the arithmetic to the geometric mean of the k smallest eigenvalues given by

$$\Gamma(k) = \frac{\frac{1}{M-k}\sum_{i=k+1}^{M}\hat{\lambda}_i}{\left(\prod_{i=k+1}^{M}\hat{\lambda}_i\right)^{1/M-k}}, \tag{31}$$

where we used the property of a determinant $det(\hat{R}_{NN}) = \prod_{i=k+1}^{M}\hat{\lambda}_i$.

The penalty function of the information theoretic criteria is determined by the number of free adjustable parameters in the likelihood function. In the following, under the hypothesis of k emitters, we examine the probabilistic model of the signal and the noise subspace component, respectively, and count the number of free adjustable parameters involved. The likelihood function of the noise subspace component, $L\{X_N\}$, contains one unknown parameter: the noise variance, σ_v^2. Then, the number of freely adjustable parameters for encoding the noise subspace component is given by $p_N(k) = 1$. The conditional distribution of the signal subspace component is determined by B_{opt} and R_w. Since the probabilistic model is conditional on the noise subspace component, the number of free parameters are determined by that of R_{SN} and R_{SS}. The sizes of R_{SN} and R_{SS} are $k \times (M-k)$ and $k \times k$, respectively. For R_{SN}, we can verify that the number of freely adjustable parameters in R_{SN} is given by $2k(M-k)$, where the factor 2 is due to the fact that the elements of R_{SN} are complex. For R_{SS}, since it denotes the covariance matrix of the signal subspace component, it is symmetric and has real diagonal elements. Then, the actual freely adjustable parameters of R_{SS} is given by $2(1+2+\ldots+k)-k = k^2$. The number of free parameters required to encode the signal subspace component is given by $p_S = 2k(M-k)+k^2$. The total number of free parameters for encoding both the signal and the noise subspace component is given by

$$p(k) = p_N(k) + p_S(k) = 1 + 2(M-k)k + k^2. \tag{32}$$

With $p(k)$, we can write the the information theoretic criteria for detecting the number of emitters as

$$C(k) = -\log L\{X_N, X_S\} + b\,[p(k), N] = N(M-k)\log\Gamma(k) + b\,[p(k), N], \qquad (33)$$

where the constant terms are ignored.

3.4 Computation procedures

The flow chart of the proposed algorithm is shown in Fig. 1. The computation procedures can be summarized as follows.

1. Align all the pulses in time relative to a reference time origin. Compute the averaged peak amplitude of each pulse and align the pulses to the point at a power level 6-dB below the peak [30].

2. Compute the sample covariance of the pulse data vector and perform the eigen-decomposition of the sample covariance matrix and arrange the eigenvalues in decreasing order.

3. Under hypothesis of different of emitters, evaluate the information theoretic criterion. Depending on the penalty function, the AIC, MDL and the Schwartz's criterion can be applied. The optimal number of emitters, $\hat{k}$, is given as the one which minimizes the criterion

$$\hat{K} = \arg\min_k C(k). \qquad (34)$$

4.0 STATISTICAL CONSISTENCY ANALYSIS

The statistical consistency is known to be one of the most important performance measures for an estimator. For a consistent estimator, the estimates converge to their true values when the number of measurements tends to infinity. In the following, we will show that the information theoretic criterion (MDL) is consistent, i.e., optimal $\hat{k}$ satisfies $\hat{k} \to K$

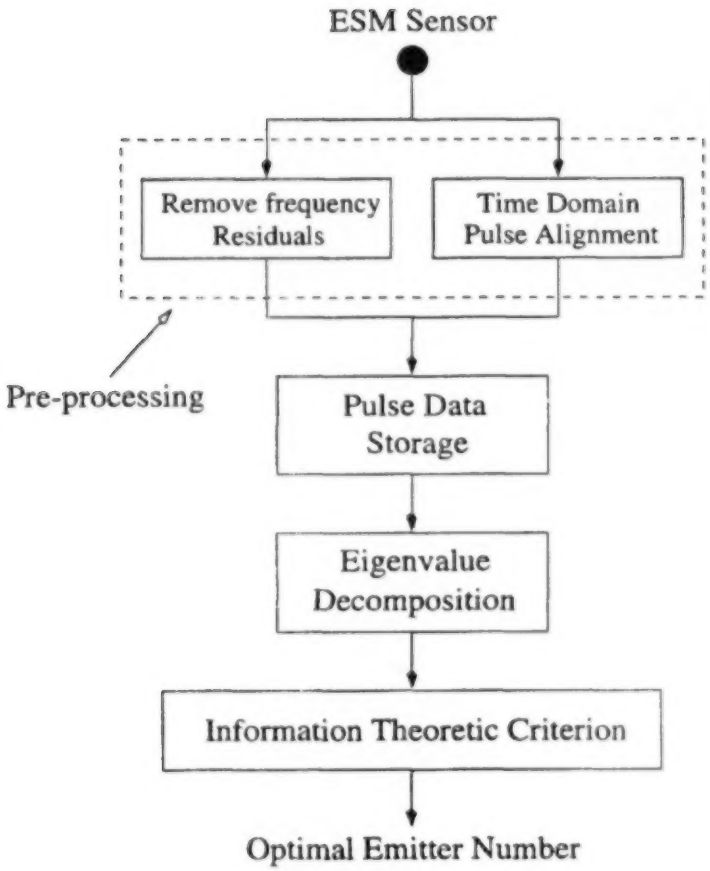

Figure 1: Computation procedures of the proposed information theoretic criterion based approach.

with probability one when the number of samples of the signal pulses, N, is sufficiently large.

Consider the sample covariance $\hat{R}_x$

$$\hat{R}_x = \frac{1}{N}\sum_{n=1}^{N}\{A\underline{s}(n)\underline{s}^H(n)A^H + A\underline{s}(n)\underline{\nu}^H(n) + \underline{\nu}(n)\underline{s}^H(n)A^H + \underline{\nu}(n)\underline{\nu}^H(n)\}. \tag{35}$$

Assume that the number of samples of the pulses is sufficiently large. Since $\{\underline{\nu}(n)\}$ is assumed to be an $i.i.d.$ Gaussian process with zeros mean and variance σ_ν^2, it is known that [27]

$$\lim_{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}\underline{\nu}(n)\underline{\nu}^H(n) \longrightarrow \sigma_\nu^2 I, \tag{36}$$

with probability one and convergence rate proportional to $O(\sqrt{\log(\log N)/N})$. Since the signal $\{\underline{s}(n)\}$ is assumed to be of finite power, using the theory of weighted sums of $i.i.d$ Gaussian random variables [28], we can verify that the following limit holds

$$\lim_{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}A\underline{s}(n)\underline{\nu}^H(n) \longrightarrow \mathbf{0}, \tag{37}$$

with convergence rate proportional to $O(\sqrt{\log(\log N)/N})$. Let $R_x = AR_sA^H + \sigma_\nu^2 I$. From (36) and (37), it can be verified that the sample covariance $\hat{R}_x$ converges to R_x with probability one when N approaches infinity. Since the signal pulse waveforms are assumed to be linearly independent, it is known that R_S has a full rank of K. It follows that AR_SA^H also has a rank of K. Using the eigen-decomposition theory, it is known that the eigenvalues of R_x are distributed as

$$\lambda_1 \geq \ldots \geq \lambda_K > \lambda_{K+1} = \ldots = \lambda_M = \sigma_\nu^2. \tag{38}$$

Since $\hat{R}_x$ is equal to R_x with probability one when the number of samples is sufficiently large, the eigenvalues of $\hat{R}_x$ equal to those of R_x [29], i.e.,

$$\hat{\lambda}_m = \lambda_m, \quad m = 1, 2, \ldots, M, \tag{39}$$

with probability one. Let $\overline{\Gamma}(k)$ be given by

$$\overline{\Gamma}(k) = \frac{\dfrac{1}{M-K}\displaystyle\sum_{i=k+1}^{M} \lambda_i}{\left(\displaystyle\prod_{i=k+1}^{M} \lambda_i\right)^{1/M-K}}, \tag{40}$$

and define the limit information theoretic criterion $\overline{C}(k)$ as

$$\overline{C}(k) = N\{(M-k)\log\overline{\Gamma}(k) + \frac{1}{N}b\,[p(K), N]\}. \tag{41}$$

It can be verified that the information theoretic criterion $C(k)$ is equal to the limit function $\overline{C}(k)$ with probability one when N approaches infinity. It follows that the optimal $\hat{k}$ also converges to minimizing $\overline{k}$ of $\overline{C}(k)$ with with probability one.

The limit information theoretic criterion $\overline{C}(k)$ has two terms: $\log\overline{\Gamma}(k)$ and the penalty function. $\overline{\Gamma}(k)$ represents the ratio of the arithmetic to the geometric means of the k smallest eigenvalues of R_x. It is known that an arithmetic mean is always larger than or equal to its corresponding geometric mean, i.e.,

$$\overline{\Gamma}(k) \geq 1, \tag{42}$$

where the equality holds only and if only all the variables are equal. The distribution of the eigenvalues of R_x is shown in equation (38). When the actual number of emitters is K, R_x has $M-K$ identical small eigenvalues. When $k \leq K$, the eigenvalues $\{\lambda_i;\ i = k+1, k+2, \ldots, M\}$ are not all equal. Thus, we have $\overline{\Gamma}(k) \leq 1$. where the equality holds only when $k = K$. It can be verified that, in (41), the second term approaches zero when $N \to \infty$ and can be ignored. It follows that, for $k \leq K$, $\overline{C}(k)$ reaches minimum when $k = K$.

For $k > K$, since all the $M-k$ smallest eigenvalues of R_x are all equal, $\overline{\Gamma}(k) = 1$

Table 1: Eigenvalue distribution of the sample covariance of the pulse data vector

	1	2	3	4	5	6	7	8	9	10
$\hat{\lambda}_i$	3.0587	0.1831	0.0164	0.0081	0.0006	0.0006	0.0005	0.0005	0.0004	0.0004

and the first term in (41) is equal to zero. Since the penalty term $b\ [p(k), N]$ is an increasing function of k, it can be shown that $\overline{C}(k)$ attains the minimum when $k = K$. Therefore, it can be concluded the limit function attains minimum if and only if $\overline{k} = K$ for all k. Since $\hat{k}$ converges with probability one to the minimizing argument of the limit function $\overline{C}(k)$, the strong consistency of $\hat{k}$ is readily established.

5.0 NUMERICAL SIMULATION STUDIES

Computer simulations and real ESM sensor data are used to demonstrate the effectiveness of the proposed algorithm. In the computer simulations, four emitters are simulated and their signal waveforms are shown in Figure 2. The signals were selected from the real intercepted radar signals. They are represented in analytic forms using in-phase and quadrature (I/Q) components. We assume that pulses have been pre-processed and aligned in time. The length of the pulses are 103, 99, 103 and 104, respectively. In the figure, (a), (c), (e) and (g) are the pulse amplitudes, and (b), (d), (f) and (h) are corresponding unwrapped pulse phases of the signals, respectively. The receiver is simulated to have a twenty percent perturbation in gain relative to its peak amplitude and a fixed phase shift uniformly distributed in $[0, 2\pi]$ for each pulse. The pulses are assumed to be uniform among the four emitters. The noise is generated as $i.i.d.$ Gaussian processes and is added to all the pulses.

Figure 3 shows an application of the information theoretic criteria to the emitter number detection problem. The standard deviation of the noise process is chosen to be 0.04. Table 1 shows the distribution of the first 10 largest eigenvalues of the sample covariance of the pulse data vector. It can be seen that the sample covariance has four relatively large eigenvalues which can be easily separated from the rest, indicating that the number of emitters is four. However, this is not always the case. In most cases, especially when the signal-to-noise ratio (SNR) is small, the boundary between the large and small eigenvalues is not so obvious and separation between them becomes difficult. In Figure 3, we use the MDL and the AIC approach and plot the values of the information theoretic criteria for different hypothesized number of emitters. Both approaches have

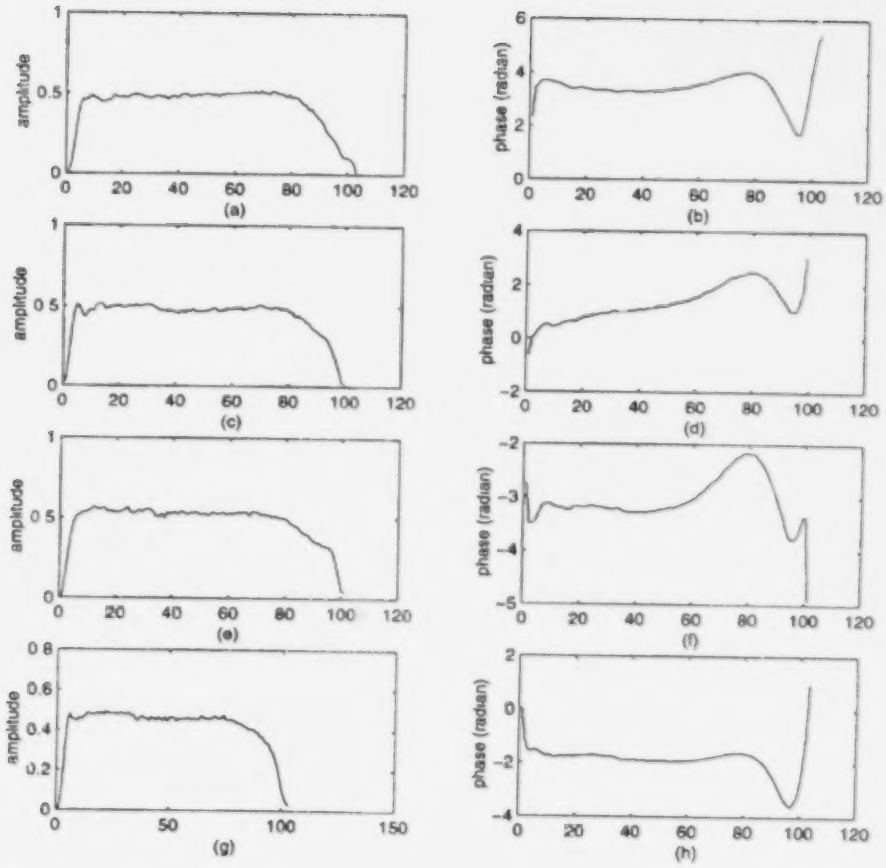

Figure 2: Pulsed signals arriving at the sensors.

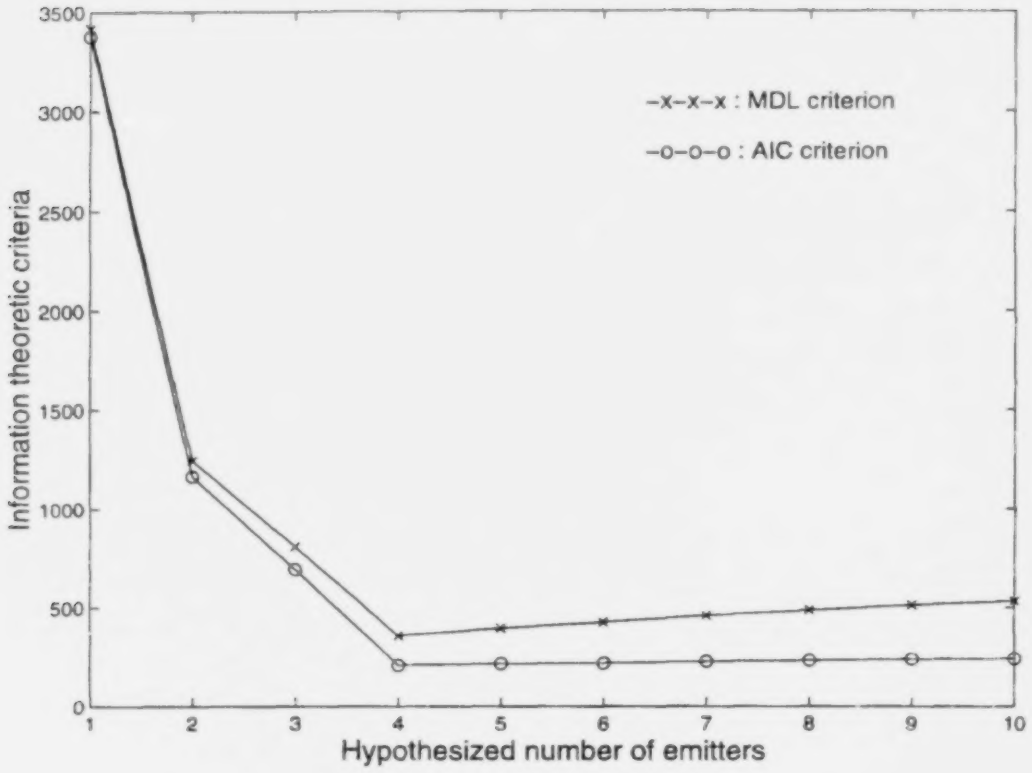

Figure 3: Information theoretic criteria via the hypothesized number of emitters.

been able to detect the correct number of emitters. They both reach the minima when the hypothesized number of emitters is equal to four.

To examine the performance of the information theoretic criteria under different standard deviation of the sensor noise, we vary the the noise standard deviation σ_ν from 0.01 to 0.15 with a step of 0.01 and apply the information theoretic criteria. For each σ_ν, the test is repeated 300 times and the number of errors are recorded. Obviously, the detection error rate can be viewed as a performance measure for the information theoretic criteria. Figure 4 shows the variation of the detection error rate via the noise standard deviations. Both the MDL and the AIC approach are tested. It can be seen that for both criteria, the detection error rate increases as the standard noise deviation increases, and they gradually approach the value 1. The AIC approach, however, exhibits an irreducible detection error rate even when the noise deviation is small. On the other hand, the MDL approach does not posses such a characteristics and has zero detection error rates when the noise standard deviation is small. This is due to the fact that the MDL criterion uses

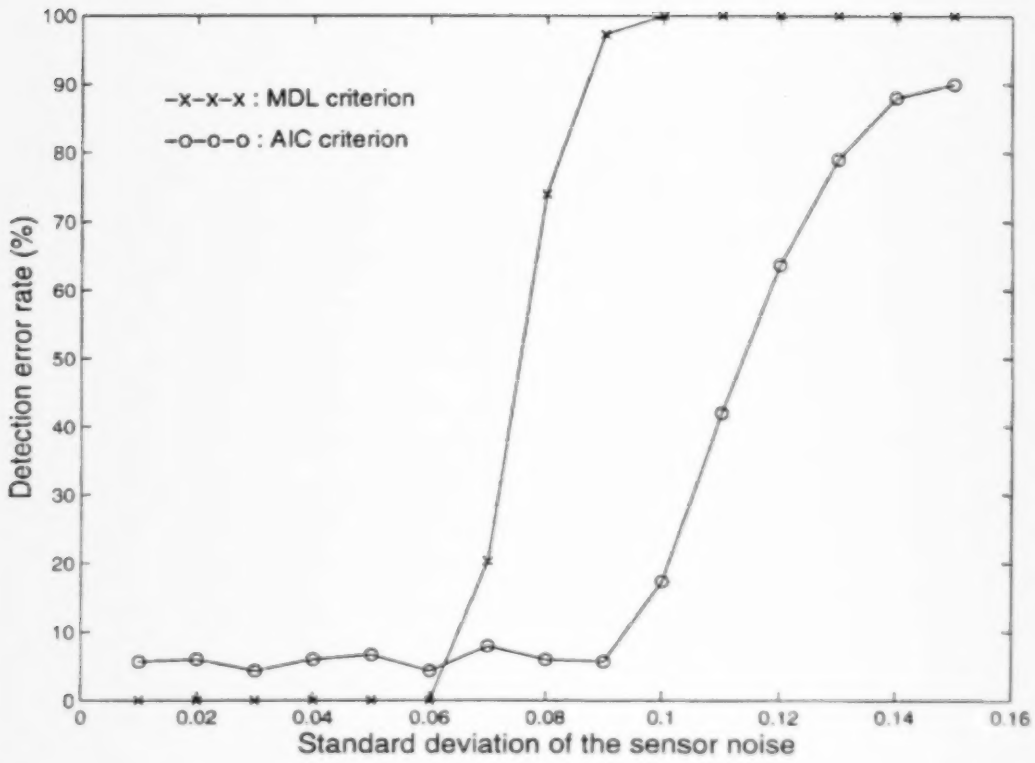

Figure 4: Variations of the detection error rate via the standard noise deviation.

a high penalty term to reduce the detection error rate. The trade-off is that the MDL criterion suffers from a higher detection error rates when the noise standard deviation is high.

To understand the efficiency of the information theoretic criteria in a practical environment, we apply real data to test the proposed approach. The data were collected using the Interferometric Intra-pulse Receiver developed at the Defence Research Establishment Ottawa (DREO) [30]. The interferometer is a four channel receiver which can provide simultaneous intrapulse analysis and high accuracy direction finding for marine and surface surveillance applications. The signal in each channel is first amplified and then mixed down with a local oscillator signal to an IF signal. The IF signals are digitized at a sampling rate of 500 MHz or 1 GHz with an 8-bit digital oscilloscopes. The digitized IF data are fed to a Hilbert transformer which comprises two quadrature FIR bandpass filters and corresponding I/Q components of the pulse are generated and stored. The frequency profile of each pulse is also obtained from the Hilbert transformer. The pulses have been deinterleaved and sorted. The pulse data are down-converted to the base-band and stored in files along with their corresponding ground truth are stored in files. However, the pulse data are usualy found to contain frequency modulation residuals and we need to remove them for the application of the information theoretic criterion.

The removal of the frequency modulation residual is done by using a linear fitting of the unwrapped phase of the pulses. Assume that the mth pulse has a frequency modulation residual of $\Delta\omega_m$. Ignoring the noise, the phase of $\tilde{x}_m(n)$ can be written as

$$\phi_{\tilde{x}_m}(n) = \Delta\omega_m n + \phi_{\tilde{\alpha}_m} + \phi_{s_1}(n - \tau_m), \tag{43}$$

where $\phi_{\tilde{x}_m}(n)$, $\phi_{\tilde{\alpha}_m}$ and $\phi_{s_1}(n - \tau_m)$ denote the phases of $x_m(n)$, $\tilde{\alpha}_m$ and $s_1(n - \tau_m)$, respectively. It can be seen that phase term caused by the frequency modulation residuals is a linear function of n, where the slope is equal to $\Delta\omega_m$. Thus, we can use a linear fitting to estimate the frequency modulation residual by

$$\{\Delta\hat{\omega}_m, \hat{\phi}_m\} = \arg \min_{\Delta\omega_m, \phi_m} \sum_{n=1}^{N} [\Delta\omega_m n + \phi_m - \phi_{\tilde{x}_m}(n)]^2, \tag{44}$$

where ϕ_m denotes the offset. Using the standard optimization procedures, we can obtain

$$\Delta\hat{\omega}_m = \frac{\frac{1}{N}\sum_{n=1}^{N} n\phi_{\tilde{x}_m}(n) - \left(\frac{1}{N}\sum_{n=1}^{N} n\right)\left(\frac{1}{N}\sum_{n=1}^{N}\phi_{\tilde{x}_m}(n)\right)}{\frac{1}{N}\sum_{n=1}^{N} n^2 - \left(\frac{1}{N}\sum_{n=1}^{N} n\right)^2}, \tag{45}$$

and the offset

$$\hat{\phi}_m = \frac{1}{N}\sum_{n=1}^{N}\phi_{\tilde{x}_m}(n) - \hat{\phi}_m\left(\frac{1}{N}\sum_{n=1}^{N} n\right). \tag{46}$$

Figure 5 plots the amplitudes and phases of one of the profiles before and after the removal of the frequency modulation residuals. After the removal, it can seen that the phases of the pulses from the same emitters converge more tightly and resemble each other more closely than before. Eight emitter profiles are used. Each time, we use $M = 40$ pulses which are selected uniformly from the radar profiles and among the pulses within each profile. Figure 6 shows the distribution of the detection rate versus the hypothesized number of emitters. Each test is repeated 300 times to obtain the detection rate. Both the MDL and the AIC are applied. The MDL has correct detection rate of around 80 while the AIC fails to provide the correct number of emitters present.

6.0 CONCLUSIONS

In this report, an approach based on the application of the information theoretic criteria has been proposed for detecting the number of emitters. The approach makes use of the intrapulse information and is capable of dealing with a complex signal environment. Computer simulations and real data tests are carried out to evaluate its performance. The approach is statistically consistent and computationally efficient. It is suitable for real-time applications. The approach does not require any subjective threshold settings: an important advantage for designing a modern intelligent ESM system. Although the implementation of the approach is currently based on a batch of signal pulses, the use of incremental procedures is under investigation which can avoid the computations involving large matrices and make the implementation adaptive.

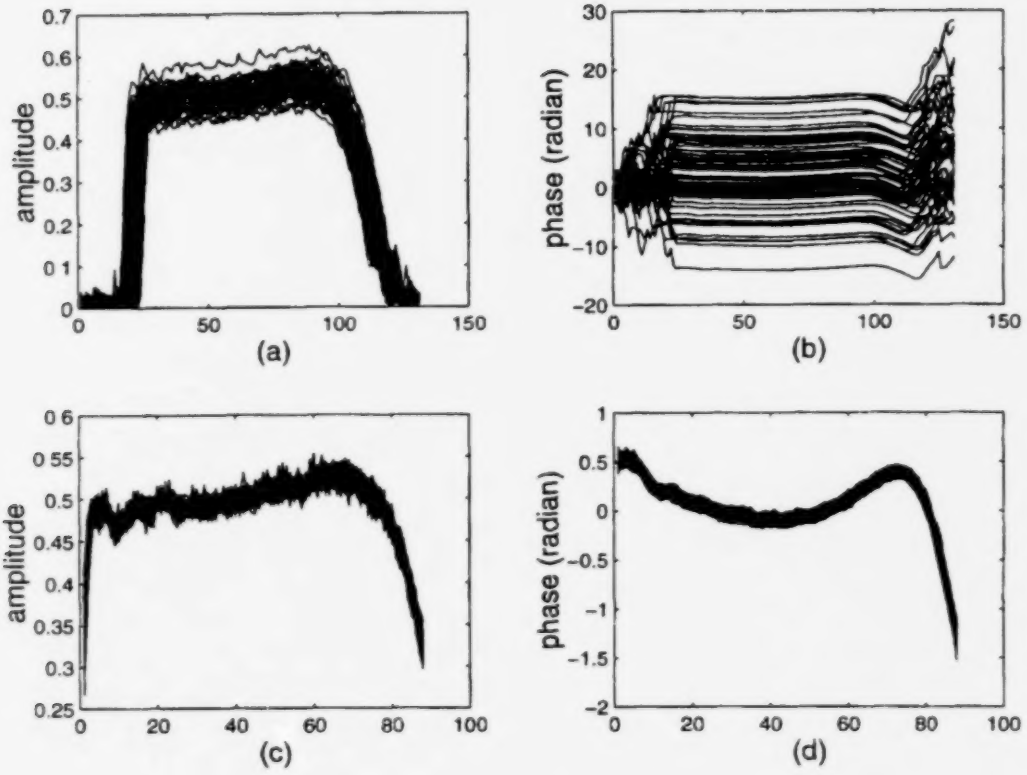

Figure 5: Amplitude and phase distribution of one of the radar data files. (a) and (b) denote the amplitudes and phases of pulses, respectively, before being pre-processed, and (c) and (d) are those after the pre-processing procedures.

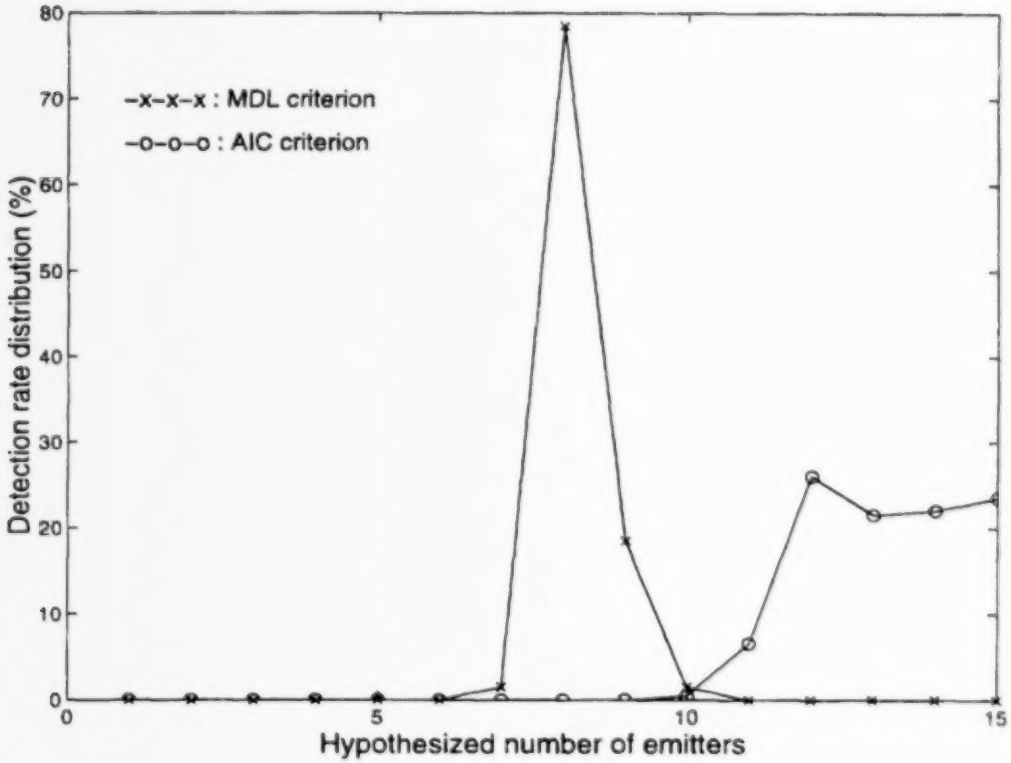

Figure 6: Distribution of the detection rate via the hypothesized number of deviation.

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Emitter Number Detection Based on Intrapulse Information and Application of the Information Theoretic Criteria (U)

4. AUTHORS (Last name, first name, middle initial)

Zhou, Yifeng and Lee, Jim P. Y.

5 DATE OF PUBLICATION (month and year of publication of document)	6a. NO. OF PAGES (total containing information. Include Annexes, Appendices, etc.)	6b. NO. OF REFS (total cit document)
February 2000	26	30

7. DESCRIPTIVE NOTES (the category of the document, e.g. technical report, technical note or memorandum. If appropriate, enter the type report, e.g. interim, progress, summary, annual or final. Give the inclusive dates when a specific reporting period is covered.)

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In Electronic Support Measures (ESM) systems, intrapulse analysis has gained much interest in the development of pulse train deinterleaving techniques due to its ability to handle complex radar signals. In this report, an approach for detecting the number of emitters is proposed based on the use of intrapulse information of the intercepted pulse trains. The approach is an application of the information theoretic criteria. It exploits the fine intrapulse modulation information of emitter signal and has the advantage of not requiring a subjective threshold setting. The approach is statistically consistent and computationally efficient. Computer simulations and real sensor data are used to demonstrate the effectiveness of the proposed approach.

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